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Factors Influencing Cotton Farmers' Perceptions about the Importance of Information Sources in Precision Farming Decisions

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Factors Influencing Cotton Farmers' Perceptions about the Importance of Information Sources in Making Precision Farming Decisions

Introduction

Precision farming (PF) is the use of site-specific technologies to obtain information for the establishment of more efficient crop management strategies, which could lead to variable rate input application that considers the locational heterogeneity within a field. More efficient crop management plans based on site specific information can decrease costs, increase profits, and mitigate environmental externalities generated from crop production (Swinton and Lowenberg-DeBoer 1998).

As agricultural technologies become more complex the demand for information on how to use these technologies also increases (Schnitkey et al. 1992; Ortmann et al. 1993). Precision farming can improve input efficiency at the cost of added complexity due to the large amounts of information that need to be processed but also adds complexity to the decision making processes because of the large amount of information to be processed. The copious information available to farmers from PF technologies often requires guidance on how to incorporate this data into management plans (Griffin and Lambert 2005). Hence, different information providers may play an important role in the decisions farmers make about precision agriculture technologies. The demand for precision farming information by farmers has been met by various private and public sources including crop consultants, farm input dealerships, Extension, and mass media channels (McBride and Daberkow 2003).

In the context of farm business decision making (e.g., marketing, production and financial decisions), several studies have focused on the effects of farmer/farm business characteristics on preferences for information sources (Schnitkey et al. 1992; Ortman et al. 1993; Just et al. 2002, 2006; Velandia et al. 2010). But previous studies have not explored perceptions about the relative importance of information sources when making marketing, production and financial decisions. Using a multinomial logit regression, Schnitkey et al. (1992) studied the factors influencing farmers use and perceived usefulness of information sources with respect to production, marketing and financial decisions. Ortmann et al. (1993) studied the factors influencing the use by cornbelt farmers of a single information source (consultants), but did not evaluate their perceptions of the relative usefulness of consultants compared with other information sources. Just et al. (2006) estimated individual probit models to determine demand for information sources but did not compare the relative importance of those sources. Velandia et al. (2010) explored the use of information sources to obtain precision farming information. Using univariate statistics, they looked at the complementary use of Extension with other information sources. Although this study suggests complementary use of information sources they did not study the relative importance of these information sources as farmers made decisions about precision farming. Despite the fact that the use of information sources may be complementary (Velandia et al. 2010) farmers may prioritize some sources over others based on the importance these sources play in decision making processes.

The objective of this research is to examine the factors influencing cotton farmer perceptions about the importance of various information sources in making precision farming decisions (e.g., e.g., adopting, abandoning or augmenting precision farming technologies). We evaluate factors affecting how farmers rank crop consultants, farm input dealerships, Extension, other farmers, trade shows, the Internet and printed news/media based on their importance in terms of making decisions about precision farming. Data from cotton farmers in Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North and South Carolina, Tennessee, Virginia, and Texas are used to achieve the objective of this study. Findings from this research may be use by information providers to evaluate cotton farmer satisfaction from the information services they provide and better tailor their precision farming information dissemination tools to the demands of target clientele. More efficient delivery of information can help farmers improve management skills and production efficiency, and in turn increase the likelihood of successful outcomes resulting from the use of precision farming technologies.

Conceptual Framework

A random utility model was used to analyze the factors influencing cotton farmer perceptions about the importance of various information sources in making precision farming decisions. Cotton producers are assumed to be rational decision makers who maximize the discounted expected benefits from farming. Producers make decisions about the sources of precision farming information they perceive to be useful for crop input management and are willing to spend time and money to collect information about a technology if economic returns are anticipated (Feder and Slade 1984; Strickland, Ess, and Parsons 1998; Plant 2001).

Producer uncertainty about incorporating precision farming information into management plans compels them to search for different information sources to identify potential benefits from incorporating any precision farming technology in their operation. Cotton producer i faces a set of alternatives, $J_i = 1,2,3 \dots \dots . . , J$, in the search for precision farming information. The utility producer i receives from alternative $j \epsilon J_i$ can be represented by a random utility model (Kennedy 1992):

(1) $$U_{ij} = V_{ij} + \varepsilon_{ij} \text{ for } j \in J_i,$$

where V_{ij} is the deterministic components of utility from alternative j and ε_{ij} is a random component. The deterministic component V_{ij} may include attributes of the alternatives considered and characteristics of the individual (e.g., age, education, household income, location, and farm size). The deterministic component is usually assumed to be linear in parameters:

(2) $$V_{ij} = \beta_j' x_i,$$

where x_i is a vector of farmer/farm business characteristics of cotton producer i; β_j is a vector of unknown parameters associated to individual i's characteristics that may vary across alternatives. In this study, attributes of the alternatives are not included because there is no information available about the attributes of the information sources considered.

Producers can compare the importance of alternative j with the importance of alternative k in making precision farming decisions such that cotton producer i will prefer alternative j over alternative k if:

(3) $$U_{ij} > U_{ik}$$

Applying the Luce and Suppes Ranking Choice Theorem to the random utility model described in (1), and assuming that j is a serial of index preferences (Chapman and Staelin

1982), the joint probability that alternative 1 is preferred to alternative 2 which is preferred to alternative 3, and so on, including all the alternatives, can be represented as follows:

(4) $$Prob\left(U_{i1} \geq U_{i2} \geq U_{i3} \geq \cdots \geq U_{iJ}\right) = \prod_{j^*=1}^{J} Prob(U_{ij^*} \geq U_{ij}) \text{ for } j = j^* + 1 \ldots J_i$$

Equation (4) is derived from the Luce - Suppes Ranking Choice Theorem which allows decomposition of the joint probability $Pr\left(U_{i1} \geq U_{i2} \geq U_{i3} \geq \cdots \geq U_{iJ}\right)$ into a series of successive and independent events where U_{ij^*} represents the utility for the most preferred alternative j^* at each stage of decision (Chapman and Staelin 1982). The right-hand side of (4) is the product of the probability of choosing alternative 1 over the other alternatives, $Pr\left(U_{i1} \geq U_{i2} \geq U_{i3} \geq \cdots \geq U_{iJ} | J_i\right)$, the probability of choosing 2 given that 1 was already selected , $Pr\left(U_{i2} \geq U_{i3} \geq U_{i4} \geq \cdots \geq U_{iJ} | J_i - \{1\}\right)$, the probability of choosing 3 given that 1 and 2 were already selected , $Pr\left(U_{i2} \geq U_{i3} \geq U_{i4} \geq \cdots \geq U_{iJ} | J_i - \{1,2\}\right)$, and so on.

Empirical Strategy

Data

This analysis uses data from the 2009 Cotton Incorporated Precision Agriculture survey (Mooney et al. 2010). This survey was mailed to 13,783 cotton producers in Alabama, Arkansas, Georgia, Florida, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, Texas, and Virginia. Using Dillman's (1978) general mail survey procedure, the initial questionnaire was mailed February 20, 2009 with a reminder post card sent two weeks later and a follow-up mailing to producers who had not responded on March 27, 2009. The list frame of cotton farmers was obtained from the Cotton Board in Memphis, Tennessee. The response rate was 12.5%.

The survey requested information about the use, profitability, and perceived benefits of precision farming technologies and farm business and farmer characteristics. In addition, farmers were asked about their opinions on the use and perceived importance of information sources to obtain precision farming information. Cotton producers were asked to rank from 1 to 7 their perceptions about the importance of various information sources for making precision farming decisions. In this question, a value of 1 corresponded to the information source that the farmer perceived as having the highest importance in making decisions about precision farming; a value of 2 corresponded to the information source with the second highest importance, and so on.

The rank-ordered logit model

Studies in psychology, economics, and marketing have used ranking data and the Rank-Ordered Logit model (ROLM) to analyze an individual's preferences over a set of alternatives (Beggs, Cardell, and Hausman 1981; Caplan, Grijalva, and Jakus 2002; Lareau and Rae 1989). The advantage of this type of data is that it provides more information about preferences when compared with data in which individuals are asked to illicit their most preferred choice over a set of alternatives or data in which individuals are asked to rate alternatives without comparison.

The response of individual i about the ranking of information sources based on its importance to make precision farming decisions is denoted by the vector $y_i = (y_{i1}, y_{i2}, y_{i3}, \dots \dots y_{iJ})$, where y_{ij} represents the rank individual i assigns to information source j. For notational purposes, ranks can also be represented as $r_i = (r_{i1}, r_{i2}, r_{i3}, \dots \dots r_{iJ})$, where r_{ij} represents the information source ranked j by individual i. The relationship between y_i and r_i can be stated as:

(5) $$y_{ik} = j \leftrightarrow r_{ij} = k \text{ for } j, k = 1,2,3, \ldots \ldots . . J$$

If a complete ranking of all J alternatives is observed, it is hypothesize that

(6) $$U_{ir_{i1}} \geq U_{ir_i 2} \geq U_{ir_i 3} \geq \cdots \geq U_{ir_{iJ}}$$

Expression (6) implies that individual i will rank higher information source j over information source k if the utility of information source j is higher than the utility of information source k.

The probability of observing rank r_i is represented as:

(7) $$Pr(r_i) = \Pr(U_{ir_{i1}} \geq U_{ir_{i2}} \geq U_{ir_{i3}} \geq \cdots \geq U_{ir_{iJ}})$$

$$= \prod_{j=1}^{J-1} \frac{\exp(V_{ir_{ij}})}{\sum_{l=j}^{J} \exp(V_{ir_{il}})}$$

Expression (7) is actually a sequential estimation of multinomial logit models; a multinomial logit model associated with the most preferred information source, a multinomial logit for the second most preferred information source over other information sources excluding the one ranked as the most preferred and so on. The probability of choosing one alternative as the least preferred given that all others were already chosen equals one. Therefore, this last term is excluded from the product in Equation (7). The log-likelihood function of the ROLM for a sample of *n* respondents is:

(8) $$\log L = \sum_{i=1}^{n} \sum_{j=1}^{J-1} V_{ir_{ij}} - \sum_{i=1}^{n} \sum_{j=1}^{J-1} \log\left[\sum_{k=j}^{J} exp(V_{ir_{ik}})\right]$$

The ROLM relies on the assumption of Independence of Irrelevant Alternatives (IIA). The IIA property implies that the relative preference between two or more alternatives is independent from all other alternatives being ranked. The IIA assumption also implies that the error terms (ε_{ij}) in Equation (1) are independent and identically distributed (IID) (Greene, 2003). Specifically, the log-likelihood function in Equation (8) assumes that the utility function from alternative information sources follows the structure in Equation (1) where the error terms follow an IID double exponential distribution.

Ranking ability of respondents

The ROLM assumes that individuals have the ability to rank all alternatives based on the utilities they receive from each choice. However, previous studies suggest that this assumption may be violated in ROLMs given that although respondents may know their preferences over all alternatives they may find the ranking task complex and time consuming (Fok, Paap, and Van Dijk 2010). Respondents may fail to present the rankings for the least preferred choices in the context of the ransom utility model (Fok, Paap, and Van Dijk 2010; Layton 2000; Allison and Christakis 1994; Lareau and Rae 1989; Hausman and Ruud 1987; Chapman and Staelin 1982). Lack of precision in ranking the least preferred choices could also be explained by the fact that respondents may pay less attention to alternatives they prefer less, they are less interested in, or those which they do not have enough information about (Fok, Paap, and Van Dijk 2010; Chapman and Staelin 1982). Ranking ability has been explored in cases where, although respondents rank all alternatives, there is uncertainty about their ability to rank the least preferred alternatives or to rank all the alternatives overall based on underlying utilities. Another possibility to consider when evaluating ranking ability is the case when there are incomplete rankings. There are three kinds of incomplete rankings: 1) ranks that are incomplete in the least preferred choices, 2) ranks that are incomplete in the middle or most preferred choices, and 3) ranks that are incomplete in all the choices. The first case consists of individuals who rank only their most preferred choices and leave the least preferred choices unranked. As it is explained above, some studies suggest that respondents pay less attention or have less information about their least preferred choices, which may lead them to rank alternatives randomly or just leave them unranked (Fok, Paap, and Van Dijk 2010; Layton 2000; Allison and Christakis 1994; Lareau and Rae 1989; Hausman and Ruud 1987; Chapman and Staelin 1982). This first type of incomplete rankings requires a modification of the log likelihood function presented in (8). In this case, the last term of the log likelihood function is the probability of choosing the last ranked item over all the unranked items (Allison and Christakis 1994). For respondents who present a complete ranking of most preferred choices, the model assumes that all unranked items are less preferred than all ranked items. These respondents can be classified as individuals who rank their least preferred alternatives randomly.

The second and third types of incomplete ranks may be difficult to handle in a ROLM. The likelihood function (Equation (8)) requires data with rankings starting from the most preferred to least prefer choices in a sequential order. This means that ranks that are incomplete on the most preferred or middle choices may not be used in the ROLM estimation. Additionally, if respondents do not rank any of the alternatives, there is no information that can be used in the ROLM estimation.

Previous studies have used different approaches to identify respondent ability to perform the ranking task by testing the stability of the rank between the most and least preferred choices (Fok, Paap, and Van Dijk 2010; Layton 2000; Allison and Christakis 1994; Lareau and Rae 1989; Hausman and Ruud 1987; Chapman and Staelin 1982). If the least preferred alternatives are not ranked based on the underlying utility model but are included in the model, the estimated parameters will be biased (Chapman and Staelin 1982). A common way to solve this problem is to include only the top k rankings that are found not to be biased. The log-likelihood function in (8) is modified accordingly:

(9) $$\log L = \sum_{i=1}^{n}\sum_{j=1}^{k} V_{ir_{ij}} - \sum_{i=1}^{n}[\sum_{j=1}^{k}\log[\sum_{l=j}^{J} exp(V_{ir_{il}})] - \log((J-k)!)]$$

It is assumed that the least preferred $J-k$ alternatives are ranked randomly. The sum of terms goes to k instead of $J-1$. The last term in (9) includes the probability of observing a particular order for the $J-k$ least preferred items. This last term is typically ignored given that only the probability of observing the first k choices is usually considered (Fok, Paap, and Van Dijk 2010). Other methods have been explored to handle ranking abilities by relaxing the assumption that k is identical for all individuals or that ranking abilities are homogenous between individuals (Fok, Paap, and Van Dijk 2010). Fok, Paap, and Van Dijk (2010) introduced heterogeneity in the ranking abilities by dividing respondents into J latent classes where individuals in the kth class, $k = 0,1,2,3, \ldots, J-1$, are able to rank the k most preferred items and the other items are ranked randomly. For this case, the log-likelihood function described in (9) is modified as:

(10)

$$\log L = \sum_{i=1}^{n} \log\{ \sum_{k=0}^{J-1} (p_k - (\log((J-k)!)) + \sum_{j=1}^{k} V_{ir_{ij}} - \sum_{j=1}^{k} \log[\sum_{l=j}^{J} exp(V_{ir_{il}})]\},$$

where p_k is the probability that individual i belongs to class k. This approach still assumes that all individuals rank all items but there are differences in their ranking ability.

An alternative case is when individuals are not able to state their preferences over two or more items and rank them in the same position. Respondents may find difficulty in ranking two or more alternatives that they consider equally attractive. Ties in rankings affect the loglikelihood function presented in Equation (8). For these observations, terms that do not present ties have the loglikelihood function presented in Equation (8), while the likelihood function for those terms that present ties varies. Allison and Christakis (1994) proposed an alternative likelihood function for ties based on marginal likelihoods. This approach assumes that respondents do have preference ordering for tied alternatives but both possibilities (i.e., a preferred to b, and b preferred to a) are equally likely. The probability of b being preferred to a and a being preferred to b is mutually exclusive. Thus, the likelihood function for two tied items in rank position *M* is:

(11)

$$\frac{e^{V_{ir_{iMa}}}}{e^{V_{ir_{iMa}}} + e^{V_{ir_{iMb}}} + \sum_{j=M+1}^{J} e^{V_{ir_{ij}}}} \times \frac{e^{V_{ir_{iMb}}}}{e^{V_{ir_{iMb}}} + \sum_{j=M+1}^{J} e^{V_{ir_{ij}}}} + \frac{e^{V_{ir_{iMb}}}}{e^{V_{ir_{iMa}}} + e^{V_{ir_{iMb}}} + \sum_{j=M+1}^{J} e^{V_{ir_{ij}}}} \times \frac{e^{V_{ir_{iMa}}}}{e^{V_{ir_{iMa}}} + \sum_{j=M+1}^{J} e^{V_{ir_{ij}}}}$$

Ranking Abilities: an alternative approach

All the aforementioned approaches allow the introduction of ranking ability differences in ROLM estimation by selecting the appropriate number of ranks or by classifying individuals into different groups based on their ranking ability. In contrast, incomplete rankings that do not present top or middle ranks (i.e. discontinuous ranks), or those that simply do not contain any information, have not been explored in previous studies. In this research, ranking abilities are defined based on individual ability to rank at least the top k alternatives, including ties. Those individuals that present discontinuous ranks or do not present any ranks at all (i.e., empty ranks) are assume not to have any ability to rank and therefore are excluded. These observations are excluded from the estimation because neither of the two cases considered (i.e., discontinuous ranks or empty ranks) can be handled by any of the likelihood functions described in equations (8), (9) or (10). A potential selection biased may be introduced in the analysis when excluding those responses from the analysis. Previous literature has explored different alternatives to correct for sample selection biased. Heckman (1979) introduced a probit - OLS two stage estimator procedure to correct for sample selection bias. Lee (1983) explored an alternative approach expanding the binary choice selectivity models to more complex censored models such as a multinomial-OLS two stage estimation procedure. Lee (1983) suggested that this approach can be expanded to more complicated polychotomous choice models. This approach is appropriate when the errors of the model of interest are assumed to be normally distributed, $N(0,1)$, and the distribution of the selection model error is arbitrary (Lee 1983). Therefore this approach may not be appropriate when the selection model is dichotomous and the errors of the model of interest have a double exponential distribution as in the current study. An alternative approach to account for the potential selection biased is to define an equation that describes ranking ability and a ROLM model that includes that estimated ranking ability as an independent variable. According to the definition of ranking ability in this study, a ranking ability model can be defined such that:

(12) $$z_i^* = \boldsymbol{w}'\gamma_i + \mu_i,$$

where z_i^* is a variable measuring respondent $i's$ ranking ability, $\boldsymbol{w}$ is a vector of variables determining individual $i's$ ranking ability, and μ_i is a random disturbance. The ranking ability is not observed but the rankings are observed such that:

(13) $$z_i = \begin{cases} 1 & \textit{if at least the top k ranks were ranked} \\ 0 & \textit{if empty or discontinous ranks are observed} \end{cases}$$

The probability that individual i ranks at least the top k choices is:

(14) $$Prob(z_i = 1|\boldsymbol{w}) = \frac{e^{w'\gamma_i}}{1+e^{w'\gamma_i}}$$

The logistic model defined in (14) has a log-likelihood function defined by:

(15) $$logL_z = \sum_{i=1}^{n}[z_i\,\boldsymbol{w}'\gamma_i - \ln\{1 + \exp(\boldsymbol{w}'\gamma_i)\}].$$

The relative preferences over various items is represented by the observed rank r_i. The observed rank for individual i can be defined as a function of farmer and farm business characteristics according to the underlying utility defined in (1) as:

(16) $$r_i = \beta_j x_i + \beta_{zj}\widehat{z}_i + \varepsilon_i,$$

where x_i is a vector of farmer and farm business characteristics, $\hat{z}_i$ is the estimated ranking ability, β_j and β_{zj} are unknown parameters, and ε_i is a random component. A full information maximum likelihood (FIML) approach for which a joint distribution $f(z, r|w, x, \gamma, \beta)$is defined for the random variables z and r may be used to estimate the parameters in (12) and (16). An alternative approach is to first estimate the parameters in (12) and then maximize the conditional log-likelihood function using the estimates from the ranking ability model (Limited Information Maximum Likelihood, LIML):

(17) $$\log L = \sum_{i=1}^{n} \sum_{j=1}^{J-1} (\beta_j x_i + \beta_{zj}\hat{z}_i) - \sum_{i=1}^{n} \sum_{j=1}^{J-1} \log\left[\sum_{k=j}^{J} exp(\beta_k x_i + \beta_{zk}\hat{z}_i)\right]$$

The LIML approach may be easier to implement than the FIML approach. The FIML model requires the derivation of a joint distribution while the LIML only requires the definition of a log-likelihood function for each model. A joint distribution for random variables distributed logistic and double exponential may be quite complex, and therefore the LIML approach may be more convenient (Greene 2000). In the same fashion, maximizing a joint log-likelihood function may be numerically more complex than maximizing two separate log-likelihood functions (Greene 2000). If LIML is used, calculations of covariance estimates for the regressors in the ROLM must address the fact that one or more regressors have been estimated, $\hat{z}_i$. Greene (2000) provides a description of a valid covariance estimator for two stage maximum likelihood estimators based on Murphy and Topel's (1985) results:

(18) $$V_2 + V_2(CV_1C^T - RV_1C^T - CV_1R^T)V_2,$$

where V_1 is the asymptotic variance matrix of $\hat{\gamma}$ based on (15), V_2 is the asymptotic variance matrix of β_j and β_{zj} based on (17), C is a matrix given by $E\left\{\frac{\partial logL}{\partial \beta_j}\frac{\partial logL}{\partial \gamma^T}\right\}$, and R is a matrix given by $E\left\{\frac{\partial logL}{\partial \beta_j^T}\frac{\partial logL_z}{\partial \gamma}\right\}$. A big challenge when using this approach with a second stage ROLM is the estimation of log-likelihood function derivatives to calculate the C and R matrices. An analytical expression for these derivatives may be complex and a numerical approximation may be required to estimate them. Given the potential problems that may be encountered when using this approach, a simpler approach is pursued here.

In the survey sampling literature, various approaches have been explored to attend to nonresponse in complex surveys. In this study, nonresponse is defined as cases where respondents provide empty or discontinuous ranks as defined in (13). This type of nonresponse is classified as an ignorable nonresponse (Lohr 1999, p. 265). The probability of responding (as defined in (14)) depends on $\boldsymbol{w}$; in other words the nonresponse pattern depends on observable covariates. Ignorable nonresponse relates to the fact that the nonresponse mechanism can be explained. Once is taken into account, it can be ignored. Lohr (1999) proposed the use of weights to adjust for nonresponse. The weights are estimated as the inverse of the product between the probability of being selected in a sample and the probability of responding. The probability of responding in this study is defined by the expression in (14). The probability of selection is assumed to be one. Therefore the weight for a respondent is $\omega_i = 1/\Phi_i$, where $\Phi_i = Prob(z_i = 1|\boldsymbol{w})$. The log-likelihood function defined in (8) is modified by ω_i such that

(19) $$\log L^* = \sum_{i=1}^{n}\sum_{j=1}^{J-1}\omega_i V_{ir_{ij}} - \sum_{i=1}^{n}\sum_{j=1}^{J-1}\omega_i \log\left[\sum_{k=j}^{J} exp(V_{ir_{ik}})\right]$$

Empirical model

Each cotton producer faces a set of alternative sources to obtain precision farming information; J_i={Farm Input Dealerships (FD), Crop Consultants (CC), University/Extension (UE), Other Farmers (OF), Trade Shows (TS), Internet (I), and News/Media (NM)}. The response of cotton producer i about the ranking of information sources based on its importance in precision farming decisions, $r_i = (r_{iFD}, y_{iCC}, \ldots\ldots)$, for all alternatives in J_i , is assumed to be a function of farmer/farm business characteristics such that:

(20)

$$r_i = \beta_{0j} + \beta_{1j} Age_i + \beta_{2j} Education_i + \beta_{3j} Land\_Tenure_i + \beta_{4j} INC150_i + \beta_{5j} Farm\_Size_i + \beta_{6j} INCFP_i + \beta_{8j} DENSITY_i + \beta_{8j} Region_{il} \; for \; j = 1 \ldots\ldots J.$$

To achieve identification, the intercept (β_{0j}) and coefficients associated with farmer/farm business characteristics must vary among alternatives. The model also requires excluding one alternative from the alternatives set and setting it as the reference alternative. A description of all variables is presented in Table 1. University/Extension sources compile all activities and sources provided by Universities to inform farmers about precision farming, including field days, workshops, and educational materials developed by Extension about precision farming technologies. News/Media sources are defined as communication channels providing precision farming information through radio, newspaper, and magazines.

Socioeconomic and demographic factors including education, age, income, percentage of income from farming, land tenure, and farm size were hypothesized to correlate with preferences for information sources in making precision farming decisions. Previous studies have evaluated the influence of human capital on the use of agricultural information sources (Just et al. 2002;

Schnitkey et al. 1992). Just et al. (2002, 2006) developed hypotheses about the complementary relationship between types of information used and human capital, hypothesizing that individuals with more education are more likely to use information sources that provide relatively unprocessed data, raw statements or facts (e.g., news/media sources), and therefore to give more importance to these sources when making precision farming decisions.

Age is also a potential determinate of preferences for information sources about precision farming technologies (Schnitkey et al. 1992). A farmer's interest in acquiring information about precision farming may decrease as age increases. As age increases, a farmer's planning horizon shortens making the farmer less likely to spend time and/or money searching for information about new technologies. Therefore, farmers may be more likely to prefer information sources that do not have an access fee such as University/Extension or other farmers when making precision farming decisions.

In this study, farmers reporting household incomes greater than $150,000 were considered high-income farmers (Walton et al. 2008, 2010). Higher income levels may facilitate access to consulting services complementing new technologies (Rogers 1983). Crop consultants and farm dealers may specialize in services complementing precision farming technologies, while Extension may focus on the needs of a particular region. Specific information about precision farming provided by crop consultants may be more detailed and customized to particular operations, but may also come at higher costs. Therefore, farmers with relatively higher incomes may be more likely to prefer crop consultants and/or farm input dealerships as information sources, when making precision farming decisions.

Less income from farming may suggest less time spent managing the farm. Therefore, farmers reporting lower levels of income from farming may prefer information sources that provide customized information, requiring less processing time (Just et al. 2002). Media sources that provide information needing additional processing to support decision-making processes may be less preferred by farmers with lower income from farming. Alternatively, farmers whose income is highly dependent on farming are more likely to prefer information sources that provide information they consider useful for management decisions even if using those sources implies increased investment in time and money (e.g., crop consultants and/or farm input dealerships).

The percentage of total acres owned over total acres farmed is hypothesized to be positively correlated with the preferences for information sources. Planning horizons may be longer for land owners relative to land renters (Soule, Tegene, and Wiebe 2000) and therefore land tenure is hypothesized to have a positive effect on preferences for some or all information sources.

Previous studies found a positive correlation between farm size and interest in precision farming technologies (e.g., Daberkow and McBride 2003). It is hypothesized that farm size is positively related to preferences for all precision farming information sources.

Location and regional variables were included to control for factors outside the farmer's management-decision context that possibly affect preferences for information sources when making precision farming decisions. Six regional variables from the USDA Economic Research Service (table 1, U. S. Department of Agriculture-Farm Resource Regions 2007) were included in the ROLM. Using the Mississippi Portal as the reference region, the five other regions, Heartland (HEARTLAND), Prairiegate (PRAIRIE), Eastern Uplands (EASTUP), Fruitful Rim

(FRUITFUL), and Southern Seaboard (SOUTHERN), were included to control for regional differences including growing seasons, prices and weather conditions (Khanna 2001).

A variable representing farm density (number of farms per acre) in the county was included to control for differences in farm distribution. Farmers in higher farm density counties were expected to interact more frequently than farmers in low farm density counties (Lambert, Wojan, and Sulivan 2009), and therefore farmers may be more likely to consult other producers as sources of precision farming information. Farm density also accounts for regional differences in average farm size. Counties with higher farm densities may have, on average smaller farms than counties with relatively low farm densities.

Ranking Ability Model

Some studies have used logit or probit models to estimate the probability of response from survey data (Whitehead, Groothuis and Blomquist 1993). The same approach could be used to estimate the probability of a respondent ranking at least his/her top k choices. A logit model is used in this study to identify factors associated with the probability of observing complete ranks or complete ranks for the most preferred choices.

The variables hypothesized to influence the probability of a respondent ranking at least his/her top k choices were age (Age), income ($INC150$), education (LHS, HS, GED, GR), acres of cotton grown ($Acres$), whether the respondent has already adopted any precision farming technology ($Adopt\_PF$), and location ($Heartland, Prairie$, $p, Frutiful$, and $Southern$). All variables are described in Table 1.

It is expected that the probability of a respondent able to rank at least their top k choices would be negatively correlated with age and positively correlated with education. Younger and more educated farmers may be more careful when answering complex questions in a survey; therefore they may be more likely to rank alternatives without leaving the middle or most preferred choices unranked. Also, the adoption of at least one precision farming technology ($Adopt\_PF$) measuring the respondent's interest in the subject of the survey, is expected to be positively correlated with the probability of ranking at least the top k choices.

Multicollinearity tests

A linear relationship between two or more independent variables can inflate variance estimates causing problems with inferences in regression analysis (Belsley, Kuh and Welsch 1980). Two methods are used to detect multicollinearity. High variances inflation factors (VIF) are a sign of multicollinearity. However, VIFs do not provide information about the group of variables involved in the collinearity, so Condition Indexes (CI) and proportions of variation (Belsley, Kuh and Welsch, 1980) were also used. High CI values between 30 and 100 indicate moderate to strong linear relationships (SAS Institute 2009), and two or more variables with high proportions of variation corresponding to a large condition index may suggest a linear relationship for these variables (Belsley, Kuh and Welsch, 1980).

Results and Discussion

Ranking Abilities

A comparison of farmer and farm business characteristics according to their ranking ability (i.e., respondents who at least rank the top k choices) were evaluated using t-tests

(Table2). Farmers who are able to rank at least the top k choices appear to be younger, obtain a higher percentage of income from farming, and farm on average more cotton acres than those presenting empty or discontinuous ranks. A higher percentage of farmers with the ability to rank at least the top k choices have adopted at least one precision farming technology, and have bachelors or graduate degrees.

A logit model was used to estimate the probability of an individual ranking at least the top k choices (Table 3). This probability is use later to adjust the ROLM for responses that include empty or discontinuous ranks. Age, all education variables, and whether the respondent has adopted at least one precision farming technology appear to be determining the probability of ranking at least the top k choices. Besides the model coefficient estimators, the third and fourth columns in Table 3 show the odds ratios and the marginal effects evaluated at the means of the variables. The maximum VIF and CI were 1.9 and 16.92, respectively, suggesting that the variances of the estimates are not inflated by multicollinearity.

As expected, age was negatively correlated with the probability of ranking at least the top k choices. Education, as a measure of a respondent's ranking ability, had a positive impact on the probability of ranking the alternative information sources based on their importance in making precision farming decisions. Specifically, for a cotton producer who has a graduate degree the odds of ranking at least the top k choices was 1.6 times larger than the odds for a cotton producer with a bachelors degree. A cotton farmer with less than a high school degree, a high school degree or a GED degree was less likely to rank at least the top k choices when compared to respondents with a bachelor's degree. Having adopted at least one precision farming technology was found to be positively associated with the probability of ranking at least the top k choices. For a cotton producer who had adopted at least one precision farming technology, the odds of ranking at least the top k choices was about 2 times larger than the odds for a producer who had not adopted any precision farming technologies. This result may suggest that farmers who adopted at least one precision farming technology were more interested in the topic of the survey and therefore read the instructions more carefully when answering complex questions.

Rank-ordered logit model

Figure 1 presents the percentage of cotton producers ranking farm input dealerships (*FD*), crop consultants (*CC*), University/Extension (*UE*), other farmers (*OF*), trade shows (*TS*), internet (*I*), and news/media (*NM*) as either the first, second or third most important source of information when making precision farming decisions (e.g., adopting, abandoning or augmenting precision farming technologies). The most popular alternative among farmers was other farmers (*OF*). About 45% of cotton producers in our sample considered other farmers as one of the top three information sources based on importance for making precision farming decisions; 43% considered farm input dealerships in the top three, and 29% considered University/Extension as one of the top three most important sources when making precision farming decisions. In contrast, trade shows, Internet and news/media were found to be the least important with between 14% and 17% of farmers considering them as one of the top three choices.

Table 4 shows the results from the weight adjusted ROLM. This model used other farmers as the reference category. Standard errors were based on a jackknife covariance estimate. Multicollinearity did not appear to be a problem given that all condition indexes were less than 30. As explained in Equation 20, for each farmer/farm business characteristic in the ROLM there are six coefficients to be estimated that are associated with the relationship of each characteristic and the odds of ranking each alternative ahead of the reference category (i.e., other farmers). These coefficients associated with each farmer/farm business characteristics were tested for joint significance with an F-test (Table 5). The coefficients associated with the age variable (AGE) were jointly significant at the 1% level. Similarly, all coefficients associated to land tenure ($LAND\_TENURE$), and farm size ($FARM\_SIZE$) were significant at 1% and 5% significance levels, respectively. The coefficients for the income variable ($INC150$) and the percentage of income from farming ($INCFP$) were jointly significant at 10% level; coefficients associated with regional variables for the Prairiegate ($PRAIRIE$) and the Southern Seaboard ($SOUTHERN$) USDA farm resource regions were jointly significant at the 1% and 5% level, respectively.

The percentage changes in odds associated with coefficient estimates are shown in Table 6. Results suggest that younger farmers were more likely to prefer University/Extension (*UE)* over other farmers (*OF*) as a source of information when making precision farming decisions. A one year increase in age increased the odds of ranking University/Extension over other farmers by 2.2%. In contrast, older farmers are less likely to prefer Internet (*I*) over other farmers when making precision farming decisions. A one year increase in age decreased the odds of ranking Internet ahead of other farmers by 3.3%. Farmers who owned a larger percentage of the acres they farm were more likely to prefer crop consultants (*CC*) over other farmers when making precision farming decisions. Specifically, a 1% increase in acres own as a proportion of total acres farm, increased the odds of ranking crop consultants over other farmers by 91.9%. A farmer with more than $150,000 in income was more likely to prefer *FD*, *CC*, *UE*, *TS*, and *I* ahead of other farmers as source of information when making precision farming decisions.

Farmers with a higher percentage of income from farming were less likely to rank trade shows and Internet ahead of other farmers when evaluating its importance in making precision farming decisions. Increasing the percentage of income from farming by 1% decreased the odds of ranking Internet ahead of other farmers by about 44.9%. Regional differences captured by the USDA farm resource regions seemed to have an impact on preferences for crop consultants compared with other farmers as a source of information in making precision farming decisions. Being located in the Prairiegate, the Southern Seaboard or the Fruitful Rim regions decreased the odds of ranking crop consultants ahead of other farmers by 76%, 45%, and 63%, respectively.

In general, regardless of farmer/farm business characteristics other farmers (*OF*) appear to be one of the most popular sources of information among cotton producers when making precision farming decisions. These results are consistent with the fact that significant estimated intercepts for each alternative were also negative (see row 1, Table 4). These results suggest that most information sources were less likely to be ranked ahead of *OF* based on their importance when making precision farming decisions. The odds of choosing news/media (*NM*) over other farmers (*OF*) was not significantly affected by any of the farmer/farm business characteristics included in the model.

Conclusions

Farmers have a number of options to obtain information about precision farming. Farmers with different characteristics may place different importance to each source when making precision farming decisions. Using a rank ordered logit model (ROLM), this study investigated the factors affecting cotton farmers' preferences for farm input dealerships (*FD*), crop consultants (*CC*), University/Extension (*UE*), other farmers (*OF*), trade shows (*TS*), internet

(*I*), and news/media (*NM*) when making precision farming decisions. Results suggest that age, land tenure, income, percentage of income from farming, and location may affect farmer perceptions about the importance of different information sources when making precision farming decisions.

The ROLM used in this study provided more information about individual preferences across sources for obtaining precision farming information than multinomial, multivariate or ordered logit/probit models. Nevertheless, the ranking data presented empty and discontinuous ranks for some observations, affecting the quality of data available to estimate the ROLM. To address this concern, observations with discontinuous ranks or empty ranks were excluded from the estimation, based on individual abilities to rank at least the top k choices. Weights were used to adjust for survey nonresponse, where nonresponse was defined for observations with empty or discontinuous ranks (Lohr 1999). The weights were estimated as the inverse of the product between the probability of being selected in a sample and the probability of responding. Older, more educated farmers who adopted at least one precision farming technology were more likely to rank at least the top k choices.

Findings from the weight adjusted ROLM point at the importance of age, land tenure, income, percentage of income from farming, and location in determining farmers' preferences over various information sources when making precision farming decisions. Information suppliers including crop consultants, farm input dealerships, Extension educators and media information providers may be able to tailor their services to clientele based on these findings. The results from the ROLM show that regardless of farmer/farm business characteristics other farmers (*OF*) was one of the most important information sources when making precision farming decisions. Results also show that cotton producers with more than $150,000 in income, who own larger percentages of the acres they farm, were more likely to prefer crop consultants over other farmers in making precision farming decisions. This result may suggest that farmers with larger incomes were more likely to be willing to pay the imply access fee for crop consultant services, and therefore to invest more resources to ensure more complete information when making precision farming decision. Additionally, farmers who own a larger percentage of the acres they farm may have longer planning horizons and therefore be willing to invest more resources in obtaining information to make precision farming decisions. High income (i.e., more than $150,000), older cotton farmer were more likely to rank University/Extension ahead of other farmers based on their importance in making precision farming decisions. These results may suggest that Extension personnel may design educational material that fits the profile of older, high income cotton farmers. This result may also imply the possibility for Extension to charge a fee for some precision farming training activities. Finally, high income cotton farmers were also more likely to prefer trade shows and Internet sources over other farmers when making precision farming decisions. In contrast, producers with a larger percentage of income from farming were less likely to rank trade shows or Internet sources ahead of other farmers in importance when making precision farming decisions.

Results from this study may help researchers to evaluate the costs and benefits of using ranking questions and the ROLM to assess respondents' preferences over a set of alternatives. It seems that younger, more educated individuals were more likely to understand the ranking question and to answer it in a way that the researcher can asses relative preferences over the alternatives. These results imply that ranking questions should be simply designed, so respondents with different skills in understanding survey questions can more easily answer ranking questions. A respondent, faced with less complex ranking question that limits the number of alternatives, would be less likely to leave alternatives unranked or to rank the randomly.

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Table 1. Definitions and Descriptive Statistics of Variables [a] (n=760)

Variable	Description	Mean
Independent variables:		
AGE	Age of producer as of 2009	52.5621
INC150	1=if Producer's income is greater than $150,000, zero otherwise	0.3553
INCFP	Percentage of income from farming	0.7441
FARM_SIZE	Owned acres plus rented acres	1314.827
LAND_TENURE	Owned acres divided by owned acres plus rented acres	0.3514
FARMDENSITY	Number of farms in the county divided by acres of crop land in the county (2007)	0.0033
HEARTLAND	1 if farm located in the Heartland USDA Farm Resource Region	0.0237
PRAIRIE	1 if farm located in the Prairegate USDA Farm Resource Region	0.4250
EASTUP	1 if farm located in the Eastern Uplands USDA Farm Resource Region	0.4250
SOUTHERN	1 if farm located in the Southern Seaboard USDA Farm Resource Region	0.2658
FRUITFUL	1 if farm located in the Fruitful Rim USDA Farm Resource Region	0.0829
MISSPORT	1 if farm located in the Mississippi Portal USDA Farm Resource Region	0.1697
ACRES	Average cotton acreage grown in 2007 and 2008	
LHS	1=if Producer has a less than a High School degree, zero otherwise	
HS	1=if Producer has a High School degree, zero otherwise	
GED	1=if Producer has a GED degree, zero otherwise	
GR	1=if Producer has a graduate degree, zero otherwise	
ADOPT_PF	1= if producers has adopted at least one precision farming technology (i.e. cotton yield monitor, soil sampling, aerial/satellite infrared imagery, soil maps, sample, handheld GPS units, COTMAN, digitized, electrical conductivity, Green Seeker, map-based, sensor-based methods to applied inputs, GPS guidance)	

[a] Variables for which the means are not reported are variables only included in the logistic regression

Table 1. Continuation.

Variable	Description	Category
Education	Describes respondent's level of education	
	No formal education	1
	Some High School	2
	Completed High School	3
	Some College	4
	Completed College	5
	Completed Graduate or Equivalent	6

Table 2. Comparison of Means for Farmer /Farm Business Characteristics Based on Ranking Abilities

Variables	$z = 0$	$z = 1$[a]
ACRES	654.756***	875.321
AGE	60.181***	52.686
INCFP	0.701***	0.746
ADOPT_PF	0.470***	0.744
HS	0.514***	0.366
BC	0.231***	0.399
GED	0.145	0.126
GR	0.047***	0.097
LHS	0.063***	0.012
INC150	0.318	0.354
HEARTLAND	0.014	0.024
PRAIRIE	0.378	0.397
EASTUP	0.035	0.037
SOUTHERN	0.286	0.264
FRUITFUL	0.077	0.087
MISSPORT	0.209	0.191

*p<0.10, **p<0.05, ***p<0.001

[a] z=1 if at least the top *k* choices were ranked, z=0 if empty or discontinuous ranks are observed

Table 3. Parameter Estimates and Marginal Effects from the Logit Model for Estimating the Factors Influencing Ability of Ranking at Least the Top k Choices

	Coef.	Std. Err.	Odds Ratio	Marginal Effects (at the means)
*Constant****	2.4264	0.3793		
ACRES	0.0001	0.0001	1.0001	0.0000
AGE ***	-0.0421	0.0056	0.9588	-0.0099
LHS ***[1]	-1.6489	0.3963	0.1923	-0.3846
HS ***[1]	-0.7563	0.1406	0.4694	-0.1782
GED **[1]	-0.4851	0.1944	0.6156	-0.1175
GR *[1]	0.4887	0.2687	1.6302	0.1075
INC150[1]	0.0227	0.1312	1.0230	0.0053
ADOPT_PF ***[1]	0.8695	0.1313	2.3858	0.2072
HEARTLAND[1]	0.5102	0.4527	1.6656	0.1107
PRAIRIE **[1]	0.3695	0.1716	1.4470	0.0856
EASTUP[1]	0.1807	0.3457	1.1981	0.0414
SOUTHERN[1]	-0.0466	0.1813	0.9545	-0.0110
FRUITFUL[1]	0.3206	0.2489	1.3779	0.0723

[1] dy/dx is for discrete change of dummy variable from 0 to 1. *p<0.10, **p<0.05, ***p<0.001.

Table 4. Parameter Estimates and Jackknife Standard Errors for the Weight Adjusted Rank Ordered Logit Models Estimating Preferences About Information Sources Use in Making Precision Farming Decisions (Base category: Other Farmers (*OF*))

	FD[a]	CC	UE	TS	I	NM
Constant	-0.7955*	-1.1422*	-2.1120***	-0.5192	-0.2648	-1.2317*
	(0.4625)	(0.6095)	(0.5501)	(0.5907)	(0.7160)	(0.6409)
AGE	0.0052	0.0080	0.0220***	-0.0099	-0.0332***	0.0011
	(0.0070)	(0.0079)	(0.0076)	(0.0081)	(0.0087)	(0.0084)
Education	-0.0087	-0.0173	0.0441	-0.1039	0.0648	-0.0888
	(0.0728)	(0.0806)	(0.0782)	(0.0752)	(0.0833)	(0.0864)
LAND_TENURE	-0.1134	0.6516**	0.1680	0.3009	-0.0148	0.2064
	(0.2267)	(0.2780)	(0.2476)	(0.2343)	(0.2626)	(0.2684)
INC150	0.3229**	0.4445**	0.2933*	0.4991***	0.4086**	0.2628
	(0.1474)	(0.1909)	(0.1727)	(0.1691)	(0.1942)	(0.1838)
FARM_SIZE	0.0002***	0.0001	0.0000	0.0002**	0.0002***	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
INCFP	0.3264	-0.0344	-0.0275	-0.5052*	-0.5956*	-0.0247
	(0.2654)	(0.3345)	(0.3129)	(0.2765)	(0.3197)	(0.3311)
FARMDENSITY	-6.6451	-24.1965	50.4753*	51.7742	31.9087	-0.1054
	(29.2425)	(38.9949)	(29.9428)	(34.4099)	(39.0585)	(36.3869)
HEARTLAND	0.3075	0.2444	-0.8102	0.1865	0.3365	0.4582
	(0.4743)	(0.4921)	(0.6190)	(0.5562)	(0.5624)	(0.6402)
PRAIRIE	-0.2537	-1.4167***	-0.8785***	-0.2622	0.0987	-0.1117
	(0.1934)	(0.2693)	(0.2564)	(0.2319)	(0.2808)	(0.2291)
EASTUP	0.2866	-0.0731	0.0945	0.4974	0.7281	0.7775
	(0.5437)	(0.5900)	(0.4311)	(0.4744)	(0.5605)	(0.5444)
SOUTHERN	-0.2488	-0.5939	0.2500	-0.3295	0.0463	-0.0900
	(0.2174)	(0.2723)	(0.2444)	(0.2524)	(0.2849)	(0.2736)
FRUITFUL	-0.4228	-0.9885**	-0.2864	-0.6455	-0.3596	-0.3987
	(0.3110)	(0.3711)	(0.2875)	(0.3403)	(0.4159)	(0.3547)
Log-L	-3956.852					
F(78,759)	10.68					
Number of Obs.	5320					
Number of Groups	760					

*p<0.10, **p<0.05, ***p<0.001.

[a] Farm Dealers (FD), Crop Consultants (CC), University/Extension (UE), Trade Shows (TS), Internet (I), News/Media (NM)

Table 5. F-tests for Joint Significance of Explanatory Variables in the Weight Adjusted Rank Ordered Logit Model Estimating Preferences about Information Source Use in Making Precision Farming Decisions (Base category: Other Farmers (*OF*))

Variables	F(6,759)	P-Value
AGE	7.02	0.000
Education	1.15	0.332
LAND_TENURE	2.33	0.031
INC150	1.85	0.086
FARM_SIZE	4.76	0.000
INCFP	1.85	0.088
FARMDENSITY	1.45	0.193
HEARTLAND	0.92	0.482
PRAIRIE	6.30	0.000
EASTUP	0.64	0.698
SOUTHERN	2.45	0.024
FRUITFUL	1.60	0.143

Table 6. Percentage Change in Odds from the Weight Adjusted Rank Ordered Logit Model Estimating Preferences About Information Sources Use in Making Precision Farming Decisions (Base category: Other Farmers (*OF*))

	FD[a]	CC	UE	TS	I	NM
Constant	-54.9*	-68.1*	-87.9***	-40.5	-23.3	-70.8*
AGE	0.5	0.8	2.2***	-1.0	-3.3***	0.1
Education	-0.9	-1.7	4.5	-9.9	6.7	-8.5
LAND_TENURE	-10.7	91.9**	18.3	35.1	-1.5	22.9
INC150	38.1**	56.0**	34.1*	64.7***	50.5**	30.1
FARM_SIZE	0.0***	0.0	0.0	0.0**	0.0***	0.0
INCFP	38.6	-3.4	-2.7	-39.7*	-44.9*	-2.4
FARMDENSITY	-99.9	-100.0	8.3×10^{23}*	3.10×10^{24}	$7. \times 10^{15}$	-10.0
HEARTLAND	36.0	27.7	-55.5	20.5	40.0	58.1
PRAIRIE	-22.4	-75.7***	-58.5***	-23.1	10.4	-10.6
EASTUP	33.2	-7.1	9.9	64.4	107.1	117.6
SOUTHERN	-22.0	-44.8**	28.4	-28.1	4.7	-8.6
FRUITFUL	-34.5	-62.8***	-24.9	-47.6*	-30.2	-32.9

*p<0.10, **p<0.05, ***p<0.001.

[a] Farm Dealers (FD), Crop Consultants (CC), University/Extension (UE), Trade Shows (TS), Internet (I), News/Media (NM)

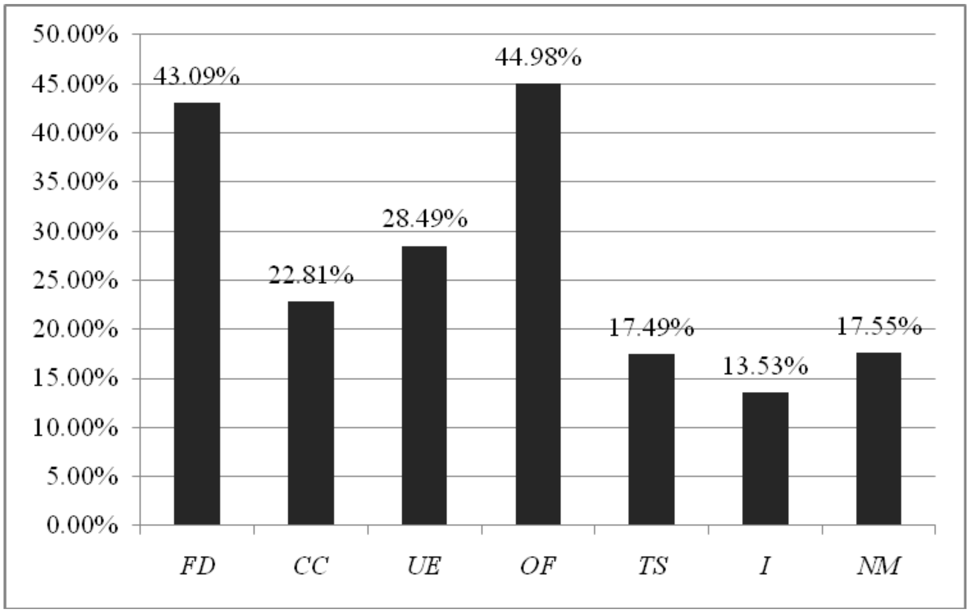

Figure 1. Percentage of Farmers Ranking Farm Dealers, Crop Consultants, University/Extension, Other Farmers, Trade Shows, Internet, and News/Media as One of the Top Three Must Important Information Sources When Making Precision Farming Decisions.